Racial discrimination in the sharing economy

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Racial Discrimination in the Sharing Economy: Evidence from Airbnb Markets across the World

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Abstract

Online peer-to-peer platforms aim to reduce anonymity and increase trust by displaying personal information about sellers. However, consumers may also rely on the names and profile photos of sellers to avoid sellers from certain social groups. Here we analyze more than 100,000 Airbnb rentals to test whether consumers discriminate against hosts from racial minorities. If consumers prefer to stay with a White host, then hosts from racial minorities should be able to charger lower prices for similar rentals. In Study 1, we analyzed 96,150 Airbnb listings across 24 cities, 14 countries, and 3 continents and found that non-White hosts charge 2.74% lower prices for qualitatively similar rentals. In Study 2, a preregistered analysis of 12,648 listings across 14 cities in the United States showed that, compared to White hosts, Black hosts charge 7.39% lower prices and Asian hosts charge 5.94% lower prices. Even though the magnitude of the price penalties varied, they emerged consistently across most cities. In sum, the current findings suggest that there is widespread discrimination against Airbnb hosts from racial minorities.

Keywords: discrimination, race, peer-to-peer markets, sharing economy, Airbnb

Racial Discrimination in the Sharing Economy: Evidence from Airbnb Markets across the World

Online peer-to-peer markets, such as eBay, Airbnb, and Uber, enable private citizens to offer various goods and service (Einav et al., 2016). One central challenge for these markets is to establish trust between sellers and potential customers, as people might be reluctant to enter the home or car of a stranger (Guttentag, 2013). Reputation systems—in which previous customers rate their satisfaction with the transaction—are a common solution to this problem. Many peer-to-peer platforms also display a wide range of personal information about sellers (e.g., names and profile photos) that are meant to reduce anonymity and increase trust (Guttentag, 2013). As Airbnb's CEO Brian Chesky put it in a press release in 2013 (Airbnb, 2013): "Access is built on trust, and trust is built on transparency. When you remove anonymity, it brings out the best in people." Yet, providing personal information about sellers can also have negative consequences, as consumers seem to rely on this information to discriminate against sellers from certain social groups (Doleac & Stein, 2013; Jaeger et al., 2019; Zussman, 2013). Here we analyze more than 100,000 Airbnb rentals across 24 cities, 14 countries, and 3 continents (total N = 108,798) to test whether consumers discriminate against hosts from racial minorities.

Racial Discrimination in Peer-to-Peer Markets

In one of the earliest studies on racial discrimination in peer-to-peer markets, Doleac and Stein (2013) investigated how a subtle cue indicating the race of a seller influenced the demand for items posted in local online markets. They found that when the same item (an iPod Nano) was held by a dark-skinned hand (vs. a light-skinned hand), advertisements resulted in fewer responses, fewer offers, and lower average and maximum offers. In a similar study, baseball cards held by dark-skinned hands attracted lower offers on eBay resulting in lower revenue for sellers (Ayres et al., 2015). These results suggest that even subtle cues to a person's race can influence economic decisions. Subsequent studies have demonstrated that these effects can be caused by various cues that indicate a person's race, such as names (Cui et al., 2020; Edelman et al., 2017; Farajallah et al., 2016; Zussman, 2013) and profile photos (Edelman & Luca, 2014; Jaeger et al., 2019). Moreover, racial disparities have been observed in various peer-to-peer markets, including eBay (Ayres et al., 2015), Uber (Ge et al., 2016), and online markets for used cars (Zussman, 2013). In short, consumers seem to rely on information that is commonly displayed on peer-to-peer platforms (e.g., names and profile photos) to discriminate against sellers from racial minorities.

Although racial discrimination seems to pervade various types of online markets, it may be particularly problematic for platforms that are part of the so-called sharing economy (Einav et al., 2016). While some markets involve little to no direct contact between sellers and buyers (e.g., eBay), sharing economy platforms like Airbnb require people to enter a stranger's home, which may be perceived as particularly risky (Guttentag, 2013). Are people less willing to stay with hosts from racial minorities? Results from a recent experiment provided support for this hypothesis: Nødtvedt and colleagues (2020) showed a fictitious Airbnb listing to a sample of Norwegian participants and manipulated whether the profile photo showed a host belonging to participants' racial in-group or out-group. Participants liked the apartment less, indicated that they were less likely to rent it, and were willing to spend less money on it when the profile photo showed that it was rented out by "Abdi" from Somalia rather than "Martin" from Norway.

Biases against Airbnb hosts from racial minorities are also reflected in the prices they are able to charge for their apartments (Edelman & Luca, 2014; Jaeger et al., 2019). In general, consumers are willing to pay a higher price for an apartment with desirable, rather than undesirable characteristics (this is the central tenet of hedonic pricing theory; Malpezzi, 2008; Rosen, 1974). For example, rentals with a private (vs. shared) room are associated with higher asking prices (Jaeger et al., 2019), presumably because consumers favor staying in a private room and are willing to pay more for it. In a similar vein, if consumers prefer to stay with a White host, then hosts from racial minorities might have to charge lower prices for otherwise similar listings to compensate for this lower demand. In other words, price disparities are indicative of consumer preferences: If consumers prefer to avoid hosts from racial minorities, prices for their apartments should be lower, all else being equal.

Edelman and Luca (2014) applied a hedonic pricing model to Airbnb rentals in New York City to examine which features (including the host's race) predict the price of listings. Their results showed that Black (vs. non-Black) hosts charge approximately 12% lower prices for similar apartments (i.e., when controlling for a host of features, such as review scores and apartment size). This effect was replicated by Jaeger and colleagues (2019), who reported a prize penalty of 10% for Black hosts in New York City. Similar price penalties were found for Asian and Hispanic hosts in San Francisco (Kakar et al., 2018) and for Asian hosts in Oakland and

Berkeley (Wang et al., 2015) The most comprehensive analysis to-date was performed by Marchenko (2019), who analyzed more than 45,000 rentals across seven cities in the United States. Again, results showed price penalties for Black and Asian hosts. Thus, both experimental studies from the lab (Nødtvedt et al., 2020) and analyses of revealed preferences in the field suggest that hosts from racial minorities experience a price penalty on Airbnb.

The Current Studies

Here we extend previous investigations on racial disparities in three central ways. First, even though prior work has found consistent evidence for racial disparities on Airbnb, the size of the observed price penalties varied substantially. For example, price penalties for Black hosts ranged from 2.3% (Kakar et al., 2018) to 12% (Edelman & Luca, 2014). This variance may be due to the fact that analyses were often based on a limited sample of listings in one or a few cities (Kakar et al., 2018; Wang et al., 2015). Even though the number of Airbnb listings is vast, researchers often have to focus on a subset of the available data (e.g., Jaeger et al., 2019; Kakar et al., 2016; Marchenko, 2019). The race of hosts is usually classified by participants, which means that the sample size of rentals that can be analyzed is constrained by the size of participant pools or research budgets. In the present studies, we avoid this problem by relying on automated procedures. Face classification algorithms show high levels of accuracy in determining demographic characteristics based on face images (Jaeger et al., 2020). Using automated procedures instead of human raters allows us to analyze a substantially larger sample of rentals than previous studies (N = 108,798).

Second, even though Airbnb operates worldwide, previous studies have only focused on one or a few cities in the United States. Thus, little is known about how widespread price penalties for racial minorities are. We address this shortcoming by analyzing 35 cities across 14 countries in Europe, Australia, and North America.

Third, analyzing a large sample of Airbnb rentals across multiple cities and countries also allows us to explore which factors explain variations in price penalties. We test whether price penalties are larger when consumers can expect to have more direct contact with the host (i.e., when renting a shared or private room as opposed to an entire listing). We also explore whether price penalties vary depending on the prevalence of hosts from racial minorities in a given city.

We report the results of two studies. In Study 1, we analyze 96,150 Airbnb rentals across 24 cities and 14 countries. In Study 2, we report a preregistered analysis of 12,648 listings across

14 cities in the United States. In both studies, we test whether non-White hosts charge lower prices for similar listings. We report how our sample sizes were determined, all data exclusions, and all measures. All data, analysis scripts, and preregistration documents are available at the Open Science Framework (https://osf.io/7pfh3/).

Study 1

In Study 1, we examined the prevalence and magnitude of racial price penalties across a wide range of Airbnb markets. Previous work has focused on discrimination against Airbnb hosts in the United States (e.g., Edelman & Luca, 2014; Marchenko, 2019). Here, we focused on the largest Airbnb markets in the world. We analyzed 96,150 rentals from 24 cities in 14 countries across Europe, Australia, and North America. Patterns of discrimination against specific racial minorities may differ substantially across these countries due to differences in racial composition and racial stereotypes. We therefore focused on countries with a White majority and examined whether hosts from a racial minority (i.e., non-White hosts) experience a price penalty. That is, we tested whether non-White hosts charge significantly lower prices for qualitatively similar rentals compared to White hosts.

Methods

Airbnb data. Inside Airbnb (http://insideairbnb.com) provides a detailed documentation of all Airbnb listing that were available in a given city on a given day. We downloaded data on all listings from cities with at least 10,000 available listings on the day the data set was created (26 April 2019). We focused on cities with a predominantly White population, which led to the exclusion of four cities with relatively large markets (Beijing, Cape Town, Istanbul, and Rio de Janeiro). The dataset contained 614,700 Airbnb listings spanning 24 cities (Amsterdam, Barcelona, Berlin, Copenhagen, Edinburgh, Florence, Hawaii, Lisbon, London, Los Angeles, Lyon, Madrid, Mallorca, Melbourne, Milan, Montreal, New York, Paris, Prague, Rome, San Diego, Sydney, Toronto, and Vienna) across 14 countries (Australia, Austria, Canada, the Czech Republic, Denmark, England, France, Germany, Italy, the Netherlands, Portugal, Scotland, Spain, and the United States).

Next, we applied our exclusion criteria. We focused on apartments (including condominiums and lofts) and houses (including townhouses) as they represent the majority of advertised listings (90.65%). Uncommon listing types (e.g., windmills and igloos) and those that indicated a more professional service (e.g., bed and breakfasts, hostels) were excluded from analysis. We only selected listings that were available for at least 7 days in the previous year and that received at least three reviews. We also filtered out hosts that had more than three listings, listings with a price of zero or a price that was more than three standard deviations above the mean price, and listings with missing data for any of our variables of interest (148,880 listings remaining). For each listing, we recorded the price per night and a host of control variables: room type (whether guests stay in a shared room, private room, or rent out the entire listing), number of bedrooms, review score, number of reviews, whether the host is a superhost, and whether the host's identity has been verified by Airbnb.

Photo classification. We used the Face++ algorithm (www.faceplusplus.com) to classify the hosts' race, sex, and age. Face++ classifies targets into four racial groups (White, Black, Asian, or Indian), two sexes (male or female), and provides a continuous age estimate. The algorithm shows good classification accuracy (although it has not been tested for Indian targets), even for more variable images like profile photos (Jaeger et al., 2020). The algorithm has been used in previous research to examine effects of demographic indicators in large data sets (Edelman et al., 2017; Kosinski, 2017). Listings with profile photos in which no face was detected or for which the algorithm could not determine the host's race, sex, and age (35.41%) were excluded from analysis, leaving a final sample of 96,150 listings.

Results

Price, location value, and number of reviews were $\log_{10}$-transformed due to their skewed distributions and all continuous variables were *z*-standardized.

Descriptive statistics. The sample size per city ranged from 647 (Mallorca) to 10,202 (Paris) with a median of 3,141 listings (M = 4,006, SD = 2,461).The median price per night was \$90 (M = \$191.49, SD = \$618.94). Most hosts were classified as White (67.66%), followed by Black (14.70%), Indian (10.92%), and Asian (6.72%). The median age of hosts was 41 (M = 42.26, SD = 13.46) and 50.37% were female. Detailed descriptive statistics for all variables can be found in the Appendix (Tables A1 and A2).

Racial price disparities. The average price of listings varied across cities, $F(23, 96126) = 4{,}657$, $p < .001$. We therefore estimated multilevel regression models with random intercepts and random slopes per city (see Table 1) using the *lme4* (Bates et al., 2015) and *lmerTest* (Kuznetsova et al., 2016) packages in R (R Core Team, 2020). For our primary analysis of interest, we predicted price with a dummy variable that indicated whether the host was classified as White (coded as 0) or non-White (i.e., Black, Asian, or Indian; coded as 1) and all control variables. This revealed a negative effect of race, β = -0.0120, *SE* = 0.0034, *t*(24.28) = 3.50, *p* = .002, 95% CI [-0.0194, -0.0046] (Model 1). Non-White hosts charged 2.74% lower prices than White hosts for similar apartments. To put this effect in perspective, a one standard deviation increase in review score was associated with a 0.82% price increase, being designated a superhost was associated with a 0.70% price increase, and the presence of an additional bedroom (which can also be seen as a proxy for the apartment's size) was associated with a 33.95% price increase.

Variation across listing. Next, we examined whether racial disparities were larger when consumers could anticipate to have more direct contact with the host. Consumers might be particularly reluctant to stay with a non-White host if they know that they will share the listing with the host (i.e., when renting a shared or private room as opposed to an entire listing). The interaction effect between race (White vs. non-White) and a dummy variable indicating whether the entire listing was rented out or whether it was shared with the host was significant, β = -0.0110, *SE* = 0.0028, *t*(54278) = 3.88, *p* < .001, 95% CI [-0.0161, -0.0056]. The price penalty for non-White hosts was larger for shared listings (i.e., shared and private room rentals), β = -0.0169, *SE* = 0.0045, *t*(17.11) = 3.76, *p* = .002, 95% CI [-0.0258, -0.0073], compared to listings that are not shared (i.e., entire home rentals), β = -0.0119, *SE* = 0.0036, *t*(25.15) = 3.30, *p* = .003, 95% CI [-0.0186, -0.0052]. Compared to White hosts, non-White hosts charged 3.97% lower prices when listings are shared and 2.70% lower prices when listings are not shared.

Table 1
The influence of host race on the price of Airbnb listings.

	Model 1	Model 2
Non-White	-0.0120 **	
Black		-0.0108 *
Asian		-0.0151 **
Indian		-0.0097 *
Female	-0.0104 ***	-0.0097 ***
Age	0.0001 **	0.0001 **
Superhost	0.0030 *	0.0031 *
Verified identity	0.0124 ***	0.0121 ***
Review score	0.0035 ***	0.0035 ***
Number of reviews	-0.0001 ***	-0.0001 ***
House	-0.0265 ***	-0.0262 ***
Shared room	-0.1195 ***	-0.1196 ***
Entire apartment	0.2814 ***	0.2812 ***
Number of bedrooms	0.1269 ***	0.1270 ***
Observations	96,150	96,150

*** $p < .001$. ** $p < .01$. * $p < .05$. † $p < .10$.

Variation across cities. Finally, we examined variation in racial price disparities across cities. A model with random slopes for the effect of race (non-White vs. White) per city showed a significantly better fit than a model without random slopes, $\chi^2(2) = 109.8$, $p < .001$, suggesting that racial price disparities varied significantly across cities (see Figure 1). Price penalties against non-White hosts were largest in New York City (-9.46%), Sydney (-8.35%), and Los Angeles (-7.61%). The sign of the penalty was reversed in four cities (Amsterdam, Milan, Prague, and Berlin), where non-White hosts actually charged slightly higher prices than White hosts. However, these effects were much smaller—ranging from +0.02% to +2.68%— than the penalties observed in other cities. These results show that price penalties against hosts from racial minorities emerge consistently across various cities and countries.

What explains variation in racial disparities across cities? Although we did not have any strong a priori hypotheses, we explored the effect of one feature that varied across different markets: the prevalence of non-White Airbnb hosts. In all 24 cities, White hosts were in the majority. However, the exact racial composition varied substantially from 46.45% non-White hosts in New York City to 19.29% in Prague. We estimated a model in which price was regressed on race (White vs. non-White), prevalence of non-White hosts, their interaction effect, and all control variables. This revealed a significant negative interaction effect, $\beta = -0.0016$, $SE = 0.0004$, $t(22.96) = 4.06$, $p < .001$, 95% CI [-0.0024, -0.0009], showing that price penalties against non-White hosts were larger in cities with a larger number of non-White hosts (see Figure 2).

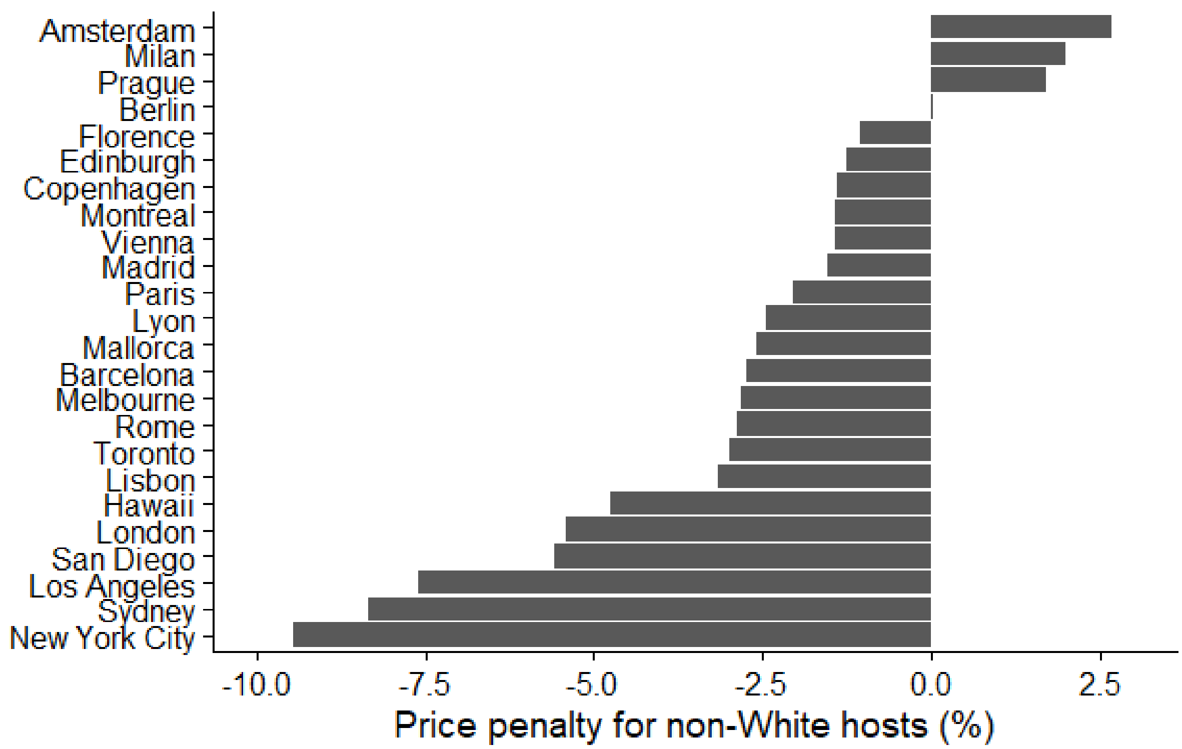

Figure 1. Price penalty for non-White (vs. White) hosts across 24 cities.

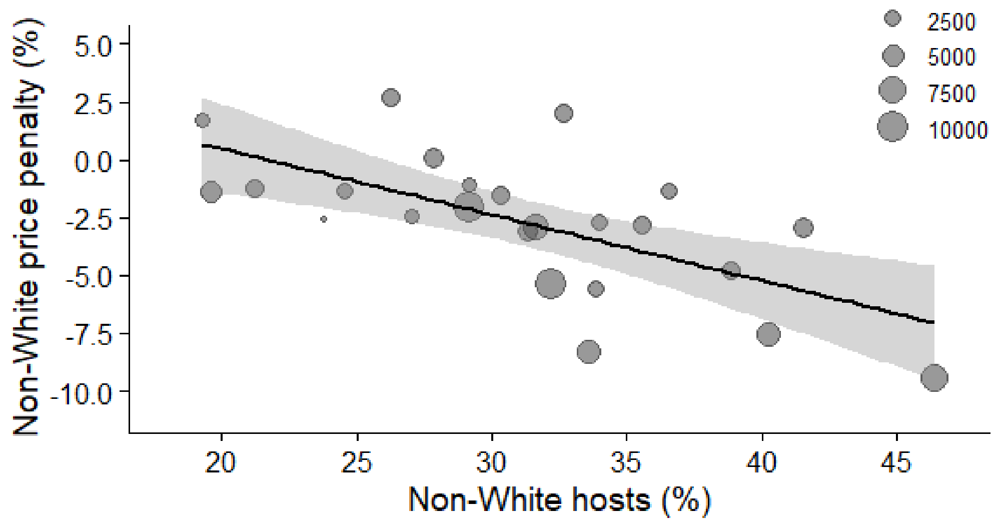

Figure 2. Correlation between a city's prevalence of non-White hosts and the observed price penalty for non-White hosts. The size of the dots denotes the number of observations for each city.

Discussion

Study 1 showed that hosts from racial minorities experience a price penalty on Airbnb: Compared to White hosts, non-White hosts charge lower prices for similar rentals. Although the size of the penalty varied, it was negative in 20 out of the 24 cities examined here. These results suggest that discrimination against racial minorities is widespread across different Airbnb markets. Price disparities were larger for rentals that were shared with the host, rather than rented out completely. This may indicate that consumers are particularly reluctant to stay with a host from a racial minority when their stay involves direct contact with the host. We also found that price disparities between White and non-White hosts were larger in markets with a relatively larger share of non-White hosts (e.g., New York City).

Study 2

The main goal of Study 2 was to provide a more precise estimate of racial price disparities in the country with the largest number of Airbnb rentals: the United States. Compared to previous investigations, which focused only on one (Edelman & Luca, 2014; Jaeger et al., 2019; Kakar et al., 2018) or a few cities (Marchenko, 2019; Wang et al., 2015), we examined a large number of Airbnb rentals in a total of 16 cities. This not only provided a more representative sample of Airbnb rentals in the United States, but also allowed us to test for variation in price disparities across different markets. Compared to Study 1, we implemented several critical methodological changes.

We relied on the Kairos algorithm (Kairos AR, Inc., www.kairos.com) to classify the race of hosts. One advantage of Kairos is that it provides confidence estimates for each classification. Focusing on rentals with hosts that could be classified with high levels confidence (i.e., at least 90%) allowed us to estimate racial price disparities more reliably by minimizing noise due to misclassified hosts. We also examined the robustness of our results by varying the classification confidence threshold. Our analysis focused on White, Black, and Asian hosts, as these categories can be classified with high levels of accuracy (Jaeger et al., 2020).

We also controlled for an additional feature of Airbnb rentals that might confound the relationship between race and price. Guests prefer to stay in rentals that are located in desirable neighborhoods (Jaeger, Sleegers, et al., 2019). Moreover, racial composition of neighborhoods can vary substantially. We therefore control for the quality of a rental's location, which may be an important confound when estimating the relationship between the race of hosts and the price of their listings. Following previous investigations (Jaeger et al., 2019; Kakar et al., 2018), we use the average rental price in a given zip code as our measure of neighborhood desirability. This study was preregistered (https://osf.io/7pfh3/).

Methods

Airbnb data. We downloaded data for 16 U.S. cities (Asheville, Austin, Boston, Chicago, Denver, Los Angeles, Nashville, New Orleans, New York City, Oakland, Portland, San Diego, San Francisco, Santa Cruz County, Seattle, and Washington D.C.) located in 11 different states and the District of Columbia (California, Colorado, District of Columbia, Illinois, Louisiana, Massachusetts, New York, North Carolina, Oregon, Tennessee, Texas, and Washington) from the Inside Airbnb website (http://insideairbnb.com). The combined data set contained 135,414 listings. Next, we applied our preregistered exclusion criteria. We focused on hosts who rent out only one property and on apartments and houses as these make up the majority of listings (87.97%). We filtered out listings that had been available for less than 10 days in the previous year and listings that had not received a review yet. We also filtered out one host with multiple accounts and one listing without a price (38,488 listings remaining). For each listing, we recorded the price per night (which constituted our outcome variable) and a host of control variables: whether the host is a superhost, whether the host's identity has been verified by

Airbnb, review score, number of reviews, property type (coded 0 for apartment and 1 for house), room type (coded 0 for private room, 1 for shared room, and 2 for entire apartment), and number of bedrooms.

We also used the Quandl API (https://docs.quandl.com/) to access rental data from Zillow (https://www.zillow.com/). For each listing, we extracted the zip code and recorded the average rent per square foot for a listing in that zip code. This served as an indicator of how listing's location desirability (Jaeger et al., 2019; Kakar et al., 2018). We excluded listings that had missing data for zip code, rental data, or any other of the aforementioned control variables (36,150 listings remaining).

Photo classification. We used the Kairos algorithm (www.kairos.com) to classify hosts' race, sex, and age. Kairos classifies targets into five racial groups (White, Black, Asian, Hispanic, and Other), two sexes (male or female), and provides a continuous age estimate. We excluded listings for which no face was detected in the host's profile photo (29,270 listings remaining). We also excluded hosts that could not be classified with at least 90% confidence and hosts that were classified as Hispanic or Other because a previous study showed that Kairos' accuracy in detecting Hispanic faces is considerably worse compared to White, Black, and Asian faces (Jaeger et al., 2020; 18,520 listings remaining). For 5,872 hosts (31.71%), more than one face was detected. For these listings, we created variables indicating whether all detected individuals are White and whether any of the detected persons was Black or Asian. For our main analyses we only focused on listings with profile photos in which one face (12,648 listings).

Results

Price, location value, and number of reviews were $\log_{10}$-transformed due to their skewed distributions and all continuous variables were *z*-standardized.

Descriptive statistics. The sample size per city ranged from 92 (Santa Cruz County) to 3,925 (New York City) with a median of 507 listings (M = 791, SD = 982). The price per night of listings ranged from \$10 to \$10,000 with a median price of \$115 (M = \$159.15, SD = \$209.32). Most hosts were classified as White (79.52%), followed by Black (10.98%) and Asian (9.50%). In all 16 cities, White hosts were in the majority, with exact percentages ranging from 69.81% in New York City to 96.74% in Santa Cruz County. The median age of hosts was 35 (M = 36.74, SD = 8.77) and 56.70% were female. Detailed descriptive statistics for all variables can be found in the Methodological Details Appendix (Tables A3 and A4).

Racial price disparities. The average price of listings varied across cities, $F(15, 12632) = 54.70$, $p < .001$, with a minimum of $104.21 in Oakland and a maximum of $272.66 in Austin. We therefore estimated multilevel regression models with random intercepts for the effect of race per city (see Table 2). A model with random slopes for the effect of race per city showed a significantly better fit than a model without random slopes, $\chi^2(5) = 89.78$, $p < .001$. In line with our preregistered analysis plan, we therefore present models that included random slopes. First, we focused on all hosts for whom Kairos provided a race classification with at least 90% confidence ($n = 12{,}648$). Regressing price on race (White vs. Black vs. Asian, with White being the reference category) and all control variables revealed negative effects for Black hosts, $\beta = -0.0333$, $SE = 0.0100$, $t(10.10) = 3.32$, $p = .008$, 95% CI [-0.0537, -0.0121], and Asian hosts, $\beta = -0.0266$, $SE = 0.0059$, $t(19.56) = 4.54$, $p < .001$, 95% CI [-0.0408, -0.0140] (see Table 2, Model 1). Compared to White hosts, Black host charged 7.39% lower prices and Asian hosts charged 5.94% lower prices for similar apartments. To put this effect in perspective, a one standard deviation increase in review score was associated with a 0.50% price increase, being designated a superhost was associated with a 3.23% price increase, and the presence of an additional bedroom (which can also be seen as a proxy for the apartment's size) was associated with a 37.53% price increase.

Table 2
The influence of host race on the price of Airbnb listings.

	Model 1	Model 2	Model 3
Black	-0.0333 **	-0.0372 **	-0.0200 *
Asian	-0.0266 ***	-0.0278 ***	-0.0230 ***
Female	-0.0052 †	-0.0046 †	-0.0022
Age	0.0007 ***	0.0008 ***	0.0006 ***
Superhost	0.0138 ***	-0.0007	0.0062 *
Verified identity	0.0076 *	0.0040	0.0050 †
Review score	0.0022 ***	0.0024 ***	0.0020 ***
Number of reviews	-0.0375 ***	-0.0004 ***	-0.0004 ***
House	0.0452 ***	0.0435 ***	0.0440 ***
Shared room	-0.1550 ***	-0.1367 ***	-0.1468 ***
Entire apartment	0.2463 ***	0.2394 ***	0.2471 ***
Number of bedrooms	0.1384 ***	0.1391 ***	0.1389 ***
Location value	0.6354 ***	0.6327 ***	0.6262 ***
Observations	12,648	16,939	19,651

*** $p < .001$. ** $p < .01$. * $p < .05$. † $p < .10$.

Variation across rentals and cities. We also examined whether racial disparities were larger when consumers could expect to have more contact with hosts. The effect of race did not vary depending on whether the entire listing was rented out or whether it was shared with the host was not significant, $F(2, 11178) = 1.82$, $p = .16$.

Next, we examined variations in racial price disparities across cities. Results from our multilevel model suggested that the effect of race on price varied significantly across the 16 cities (see Figure 3). Price penalties against Black hosts were largest in Austin (-12.11%), Washington D.C. (-11.95%), and San Diego (-10.15%) and smallest in New York City (-2.00%), New Orleans (-2.44%), and Chicago (4.73%). Price penalties against Asian hosts were largest in Austin (-9.75%), Nashville (-8.12%), and Asheville (-8.09%) and smallest in Oakland (-2.93%), New York City (-3.54%), and Denver (-3.78%). Crucially, price disparities in favor of White hosts emerged in all 16 cities. We again examined whether racial disparities were larger in cities with a larger share of non-White hosts. The effect of race did not vary as a function of the percentage on non-White hosts in a city, $F(2, 17.6) = 1.01$, $p = .39$.

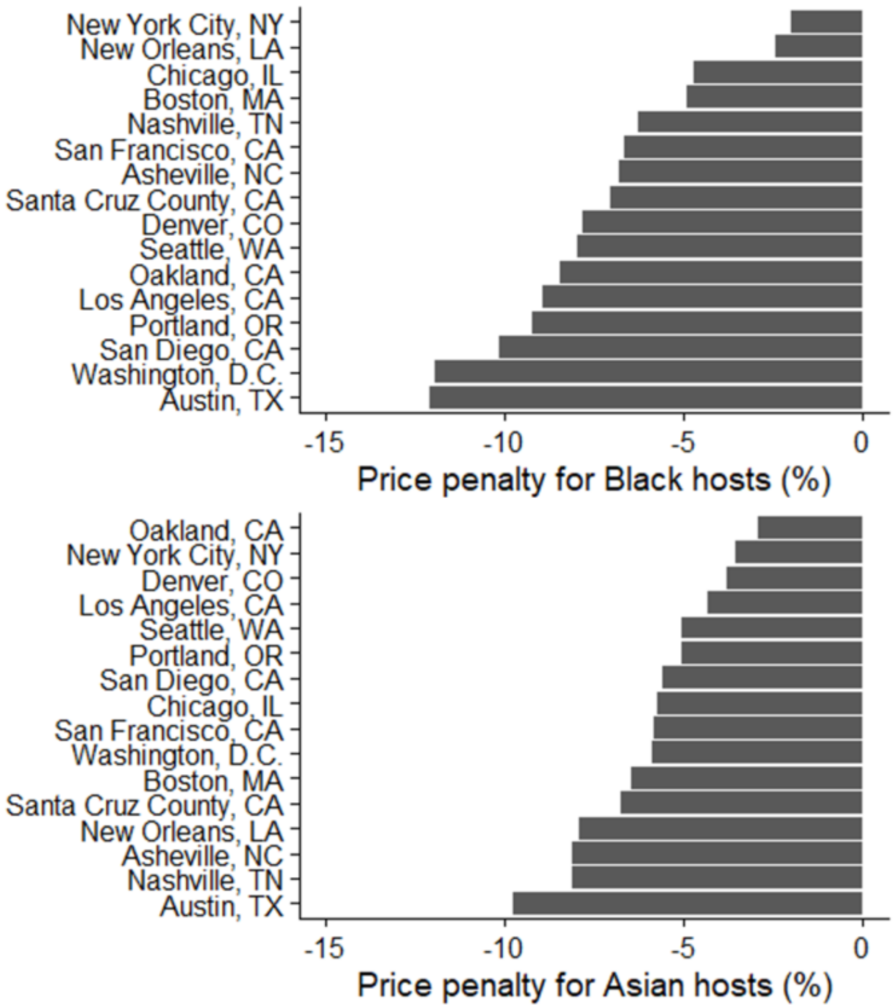

Figure 3. Price penalties for Black (top) and Asian hosts (bottom; vs. White hosts) across 16 cities in the United States.

Robustness checks. Finally, to test the robustness of our findings, we examined how implementing different inclusion criteria or coding schemes influenced the observed price penalties. Rather than excluding rentals with photos in which multiple faces were detected, we retained them and coded whether any Asian or any Black person was detected in the photo (again using the 90% confidence coding; n = 16,939 listings). We estimated another regression model in which we predicted price with two dummy variables indicating whether the photo contained a

Black person (vs. only White people) or an Asian person (vs. only White people). This revealed negative effects for the presence of a Black person, β = -0.0372, *SE* = 0.0098, $t(10.76) = 3.81$, $p = .003$, 95% CI [-0.0577, -0.0163], and for the presence of an Asian person, β = -0.0278, *SE* = 0.0047, $t(28.91) = 5.90$, $p < .001$, 95% CI [-0.0386, -0.0174] (see Table 2, Model 2). Compared to White hosts, hosts with profile photos that depicted at least one Black person charged 8.21% lower prices. Hosts with profile photos that depicted at least one Asian person charged 6.20% lower prices.

Next, we implemented more liberal exclusion criteria. Instead of focusing only on hosts whose race could be classified with at least 90% confidence, we assigned hosts the racial group that was detected predominantly (i.e., with the highest level of confidence; n = 19,651 listings). This again revealed negative effects for Black hosts, β = -0.200, *SE* = 0.0079, $t(9.90) = 2.53$, $p = .030$, 95% CI [-0.0369, -0.0042], and Asian hosts, β = -0.0230, *SE* = 0.0047, $t(12.11) = 4.87$, $p < .001$, 95% CI [-0.0332, -0.0125] (see Table 2, Model 3). Compared to White hosts, Black host charged 4.51% lower prices and Asian hosts charged 5.17% lower prices.

Discussion

Replicating the results of Study 1, we again found that hosts from racial minorities experience a price penalty on Airbnb: Compared to White hosts, both Black and Asian hosts charge lower prices for similar rentals. Results were robust when employing different inclusion criteria and confidence thresholds for the classification of hosts' race. Although the size of the penalty varied for both Black and Asian hosts substantially, it was negative in all 16 cities examined here. These results suggest that discrimination against racial minorities is common across different Airbnb markets in the United States.

General Discussion

Online peer-to-peer markets often display profile photos of sellers in order to reduce anonymity and enhance trust between consumers and sellers (Einav et al., 2016; Guttentag, 2013). However, providing personal information about sellers may come at a cost: Previous study suggest that consumers use this information to discriminate against sellers from racial minorities (Doleac & Stein, 2013; Marchenko, 2019). For instance, a recent study found that participants indicated a lower willingness to pay for the same Airbnb apartment when it was advertised by a host from a racial minority (Nødtvedt et al., 2020). In line with these findings, our analysis of more than 100,000 rentals across 24 cities, 14 countries, and 3 continents showed consistent evidence for discrimination against hosts from racial minorities. Non-White hosts charge significantly lower prices for qualitatively similar apartments compared to White hosts. Together, these results suggest that people prefer to stay with White Airbnb hosts, which may result in a price penalty for hosts from racial minorities. Our results suggest three general conclusions.

First, discrimination against Airbnb hosts racial minorities is widespread. In Study 2 (*n* = 12,648), we analyzed data from a wide range of cities across the United States (the country with the most Airbnb rentals worldwide) and found price penalties of 7.39% and 5.94% for Black hosts and Asian hosts, respectively (compared to White hosts). These results show that previously observed racial price disparities (Edelman & Luca, 2014; Kakar et al., 2018; Marchenko, 2019) replicate when analyzing a larger and more representative set of U.S. markets. Going beyond the results of previous studies, our results show that this effect also generalizes beyond the United States. In Study 1 (*n* = 96,150), we focused on the largest Airbnb markets worldwide (e.g., Paris, London, Rome, Sydney, and Berlin) and found that, on average, hosts from racial minorities charge 2.74% lower prices for qualitatively similar apartments.

Second, price penalties for hosts from racial minorities not only generalize beyond the United States, but are also common when comparing different Airbnb markets. We found price penalties for non-White hosts in 20 out of the 24 cities that were analyzed in Study 1. In a similar vein, price penalties for Black and Asian hosts emerged in all 16 U.S. cities that were analyzed in Study 2. These results suggest that discrimination against racial minorities is prevalent across different countries and cities.

Third, although we consistently found price penalties for non-White hosts, the exact size of the penalty varied. We were particularly interested in examining whether price penalties would vary depending on whether a rental is shared or not. If price penalties reflect consumers' reluctance to stay with a non-White Airbnb host, then this penalty might be stronger when guests share the listing with the host, rather than rent it out entirely. In other words, potential guests might be particularly reluctant to stay with a host from a racial minority when they anticipate to have more direct contact with the host. Results of Study 1 showed evidence for this hypothesis: Price penalties for non-White hosts were significantly larger for rentals that were shared. We also explored whether price penalties varied depending on the prevalence of non-White hosts in a given city. In Study 1, we observed stronger racial price disparities in cities with larger numbers of non-White hosts. It should be noted that similar effects were not observed in Study 2, which may have been due to the smaller sample size or the exclusive focus on rentals in the United States.

Together, our results suggest that discrimination against Airbnb hosts from racial minorities is widespread. Peer-to-peer platforms often highlight that providing personal information about sellers is crucial to foster trust between consumers and sellers (Airbnb, 2013; Guttentag, 2013). However, a growing number of studies suggest that people rely on personal information such as names (Edelman et al., 2017; Farajallah et al., 2016) and photos (Ayres et al., 2015; Marchenko, 2019) to discriminate against sellers from racial minorities. This is particularly problematic because the relatively low barriers to becoming a seller may make peer-to-peer markets particularly attractive to economically disadvantaged groups (Dillahunt & Malone, 2015; Einav et al., 2016).

Limitations and Future Directions

Our analyses focused on a wide range of countries in Europe, Australia, and North America. This allowed us to test how generalizable price penalties for racial minorities are, but it also introduced substantial heterogeneity in which racial groups were represented in our data set. Even though we focused on countries with a White majority, their exact racial compositions differed substantially. While our data show that non-White hosts experience price penalties across various cities and countries, more cross-cultural studies are needed to map which racial groups are affected most in each country. Results of Study 2 provide first insights into this question, showing discrimination against both Black and Asian hosts in the United States.

In the present investigation, we relied on face classification algorithms to code the race of Airbnb hosts based on their profile photo. Using automated procedures instead of human raters has several key advantages. For instance, coding a large number of hosts requires many participants and previous work often focused on a subset of all available rentals in one or a few Airbnb markets due to limitations in participant pool size (Jaeger et al., 2019; Kakar et al., 2018). Relying on automated procedures circumvents this problem and allowed us to examine large samples of rentals across many different markets. Yet, relying on algorithms also has disadvantages. The algorithm that was used Study 1 classified hosts into four categories; White, Black, Asian, and Indian. This may not capture all racial groups in a given country. Moreover, race classification algorithms rely on perceptual cues that are easily detectable and discriminate between different racial groups (e.g., skin color). Previous studies found relatively high levels of accuracy in race classification, especially for Black and White targets (Jaeger et al., 2020; Rhue & Clark, 2016). However, accuracy may be lower for racial groups that are more perceptually ambiguous (i.e., not characterized by unique and easily detectable facial characteristics). Given these potential limitations, we decided to focus on the broader, but more accurate distinction between White and non-White hosts in Study 1. Moreover, in Study 2, we only focused on hosts that were classified with high confidence to reduce measurement error.

More research is needed to understand variation in price penalties across different markets. For example, in Study 1, price disparities between White and non-White hosts were largest in New York City and smallest in Amsterdam. In general, we observed larger price disparities in cities with a large percentage of non-White hosts. However, these results should be interpreted with caution. It is questionable whether city- or country-level characteristics should meaningfully predict the size of these penalties. Price disparities are driven by differences in consumer demand (Malpezzi, 2008; Rosen, 1974). Thus, at least in the context of Airbnb, differences in racial discrimination are not necessarily due to different socio-economic characteristics of New York City versus Amsterdam or the United States versus the Netherlands. Rather, they should be primarily driven by the characteristics of consumers that search for rentals in these cities. Thus, it may be more fruitful to explore which characteristics of consumers predict racial preferences in online peer-to-peer markets. For instance, Nødtvedt and colleagues (2020) found preferences for White Airbnb hosts among conservative and moderate participants, but not among liberal participants.

Conclusion

In sum, the current results suggest that consumers discriminate against Airbnb hosts from racial minorities. Our analysis of more than 100,000 Airbnb rentals across 24 cities, 14 countries, and 3 continents showed consistent price penalties for non-White hosts. Crucially, we found that price penalties are larger when rentals are shared with hosts, that is, when consumers can anticipate to have more direct contact with their hosts. Although the exact size of the price penalties varied across different cities and countries, price penalties for racial minorities emerged in 20 out of the 24 largest Airbnb markets worldwide and in 16 out of 16 U.S. cities examined here. In other words, racial discrimination against non-White Airbnb hosts is widespread.

Appendix

Table A1

Descriptive statistics for all continuous variables in Study 1.

Variable	M	SD	Min	Max	Median
Price	164.88	233.77	1.00	1,757.00	90.00
Age	42.26	13.46	1.00	98.00	41.00
Review score	95.13	5.07	20.00	100.00	96.00
Number of reviews	43.80	56.85	3.00	754.00	23.00
Bedrooms	1.39	0.88	0.00	10.00	1.00

Table A2

Descriptive statistics for all categorical variables in Study 1.

Variable	Group	*N*	%
Race	White	65,054	67.66
	Black	14,135	14.70
	Asian	6,457	6.72
	Indian	10,504	10.92
Gender	Male	47,720	49.63
	Female	48,430	50.37
Superhost	Yes	33,585	34.93
	No	62,565	65.07
Verified identity	Yes	42,047	43.74
	No	54,103	56.27
Property type	Apartment	79,050	82.22
	House	17,100	17.78
Room type	Private	28,194	29.32
	Shared	504	0.52
	Entire listing	67,452	70.15

Table A3
Descriptive statistics for all continuous variables in Study 2.

Variable	M	SD	Min	Max	Median
Price	159.15	209.32	10.00	10,000.00	115.00
Age	36.74	8.77	19.00	72.00	35.00
Review score	95.25	6.30	20.00	100.00	97
Number of reviews	27.81	39.72	1.00	574.00	13.00
Bedrooms	1.33	0.91	0.00	10.00	1.00
Location value	2.64	1.23	0.69	5.92	2.33

Table A4
Descriptive statistics for all categorical variables in Study 2.

Variable	Group	N	%
Race	White	10,058	79.52
	Black	1,389	10.98
	Asian	1,201	9.50
Gender	Male	5,504	56.48
	Female	7,144	43.52
Superhost	Yes	2,965	23.44
	No	9,683	76.56
Verified identity	Yes	9,518	75.25
	No	3,130	24.75
Property type	Apartment	7,897	62.44
	House	4,751	37.56
Room type	Private	4,340	34.31
	Shared	180	1.42
	Entire listing	8,128	64.26

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